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METHODOLOGICAL PAPER

Accessing the influence of strategic marketing research on generating impact: moderating roles of models, journals, and estimation approaches

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Abstract Although the literature debates the sophistication and contributions of statistical/econometric models to strategic findings, there is a lack of understanding of how different model types contribute to the impact of strategic marketing research. We collected data from 485 studies published in top-tier marketing journals over the last 50 years to assess the influence of core strategy areas, and the moderating roles of models, journals, and estimation approaches on the impact of strategic marketing research, measured in terms of citations of the articles. Using descriptive and regression analyses, we find that strategy research focusing on the "customer" and "other areas" had a relatively greater impact, whereas "sales" had a relatively lesser impact on citations than the "4Ps strategy area." Linear regression, multivariate analysis, and structural equation models had a significantly higher impact on citations than other models. We also find that linear models and SEM positively and analytical models negatively moderate the relationship between strategy research focusing on "customer" and citations. Further, linear, analytical models and multivariate analyses negatively moderate the relationship between "sales" and citations. While strategy-focused journals positively moderate the relationship between strategic research focusing on "other area" and citations, it has a negative impact on the relationship between strategic research focusing on "sales" and citations. Relationship between strategy research focusing on "customer" and "other areas" and citations respectively is positively moderated by the estimation approach. Our study provides a perspective to the "rigor vs. relevance" debate in strategic marketing research.

Keywords Strategic marketing research · Statistical/econometric models · Journal types · Estimation approaches · Citation · Strategic contributions

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Introduction

In his recent editorial in the *Journal of Academy of Marketing Science*, Houston (2016) questions if the word *strategy* has become "taboo." The proportion of student fellows at a Doctoral Consortium who identify as "strategy scholars" has dropped from 47.2% to a distinct minority of 17.9% in just 20 years, reflecting concerns about the declining trend in the research of substantive issues that fall within the topical domain of strategic marketing. While scholars agree with the importance of "rigor" in studies (e.g., Reibstein et al. 2009; Varadarajan 2010), scholars also hold the opinion that rigor in the name of method sophistication should not eliminate the novelty of an idea of strategic importance and/or disregard the practical implications of the study (e.g., Houston 2016; McAlister 2016). Although an improvement in the methods and toolkits is desirable for the advancement of the field of marketing, other desirable characteristics such as strategic contributions to academia and practice, relevance, communicability, and simplicity should not be downplayed (e.g., Lehmann et al. 2011). In such a context, Moorman (2016) warns that first and foremost a study should make contributions, which is rarely, if ever, determined by the choice of methods. Value of an idea and its strategic contributions are critical and should be given due regard by the marketing community (Moorman 2016).

In addition to the trend of declining research of issues of strategic importance, there has been a critical discussion among the marketing academic community about whether marketing is losing its way (Reibstein et al. 2009). This discussion brings concern about the growing gap between the interests, standard, and priorities of the academic researchers and the needs of marketing executives in the boardroom as well as in the field (Reibstein et al. 2009). This gap is detrimental to the health of the long-term growth of the academic marketing field, as echoed in multiple studies (Reibstein et al. 2009; Lehmann et al. 2011).

The debate on what the approach of a marketing scholar should be, and what should get the preference in the marketing domain—methodological sophistication or strategic insights—is complicated, and there is no one answer to such a debate. While we agree with Reibstein et al. (2009) that the role of academic marketing is not only to enhance contributions in the theoretical and methodological domain but also to address "strategic issues," there is insufficient evidence to show how and what generates the strategic insights in strategic marketing studies. Hence, in this study, we attempt to provide additional insights that the marketing community deems "needful" and contributes to "strategic marketing research" so that it does not lose its importance across academics or the industry. Simultaneously, we intend to evaluate the contributions of different strategy areas and moderating roles of statistical/econometric models (hereafter "models"; e.g., linear regression model, choice models, structural models) to the impact of strategic marketing research.

We used descriptive statistics and regression analysis in order to show the relative impact of strategy areas in generating impact. We tested the moderating role of different models on the relationship between core areas of a research study (e.g., customer strategy, firm strategy) and the performance of the article, measured in terms of the citations. Further, we also examined how the journal type and the estimation approach used in the article moderate the relationship between core area of the study and the performance of that study.

We collected data from 485 studies published in top-tier marketing journals across different sub-domains such as pricing, distribution, promotion, etc. We first looked at the different models used across articles published in marketing journals and came up with a comprehensive list of models. We coded the studies for different models, journals, sub-domains, and other relevant variables available in the studies. We counted the number of citations (Google Scholar and Web of Science) in each of these articles and the number of strategic contributions (e.g., an article is providing insights on creating new customer segments with tiered pricing strategies) and modeling (e.g., an article is developing a relevant approach to account for endogeneity) insights they are providing to the literature. Our understanding of the use of "citations" as a measure of impact is driven by the existing literature. McFadyen and Cannella (2004) mention that "citation count measure can be used to estimate the impact of knowledge created." They also opine that citations reflect the "size, nature and growth rate of a field." Further, Bogner and Bansal (2007) note that citation counts are indexes of relative importance. Finally, citations are measurable, and used as an index to decide on many academic and practitioner awards in the domain of marketing. We used descriptive analysis as well as regression models to generate the findings.

Data collected using the articles show that linear regression, multivariate, and structural equation models had a significantly greater impact on citation generation than other models, after controlling for journal type, estimation approaches, data sources, nature of the study, market setting, and age of the articles. Although the "sales strategy" area had a relatively (but not in absolute terms) lower impact on citations, we find that "customer" and "other areas" had a relatively higher impact on citation with respect to the "4Ps strategy" area. Results further show that linear and structural equation models used in the strategy research focusing on "customer" had a greater impact on citations than that of other models. However, analytical models used in the customer strategy domain could not generate a greater impact than other models. Results further suggest that SEM models used in the "other area" (e.g., innovation, international marketing, social media, firm, branding) did have a greater impact on citations than other models. Finally, linear, multivariate analysis, and analytical models used in the "sales strategy" area had a significantly lower impact on citations than "other models" (e.g., dynamic models, learning models, panel data, choice models, time series analysis). Although the complex estimation approach did not have a significant impact on citation, the complex estimation that was used in strategy research focusing on "customer" had a greater impact, whereas the complex estimation used in the sales strategy area had a relatively lower impact on citations than the "4Ps strategy" area. We also found that the strategy-focused journals were capable of generating more citations than the quant-focused journals.

This study has several contributions to the literature. First, it clarifies our understanding of whether "modeling sophistication" had played a role in deriving strategic findings. Consistent with Moorman (2016), we find that simpler models have been impactful in generating citations. This also enhances our understanding that relevance can be obtained even with simpler but rigorous models. Further, our research shows that *proper alignment between core strategy areas and models could be influential in generating better performance*. Second, computational complexity (in terms of complex estimation as well as complex models) is not always necessary for strategic marketing research. Third, although obvious, strategy-focused journals are more impactful in generating citations than quant-focused journals. Finally, this study demonstrates that in order to make "marketing's impact on businesses" more meaningful, it is time to revisit our modeling approaches that were used to derive strategic findings. This is first study to empirically validate that different strategy areas and models can have a differential influence on offering strategic insights after controlling for other factors.

This study is organized in the following manner. In the second section, we discuss what strategic marketing research is. In the third section, we discuss the classifications of different empirical models. We discuss the empirical context of the study in the subsequent section. In the fifth section, we state our results, followed by the contributions of this study. We conclude our study with potential limitations as well as future research directions.

What is strategic marketing research?

To better understand what strategic marketing research is, we need to evaluate the nuances between strategic marketing and marketing strategy through the literature review. "The marketing strategy research is broadly defined to include all firm-level strategic marketing issues, decisions, and problems" (ELMAR 2009). Marketing's strategic contributions/decisions can be viewed as an organization's decisions in the realm of marketing that leads to major consequences from the standpoint of performance—ranging from the best to the worst (Varadarajan 2010). Performance can be short term or long term and may be from any sub-domain such as pricing, sales, distribution, promotion, product, etc. Although the ELMAR (2009) definition does not focus on the customer's side of the story, it is important to include it for two reasons: first, a firm's performance is largely dependent on its customers' cash flow, and second, the process of acquiring and retaining customers is a dynamic process. Hence, defining marketing strategy as *strategic marketing* issues at all levels in a firm seems complete (Varadarajan 2010).

From a practical viewpoint, we can understand marketing strategy as "an organization's integrated pattern of decisions that specify its crucial choices concerning products, markets, marketing activities, and marketing resources in the creation, communication, and/or delivery of products that offer value to customers in exchanges with the organization and thereby enables the organization to achieve specific objectives" (Varadarajan 2010). Marketing strategy is the set of integrated decisions and actions (Day 1999) by which a business expects to achieve its marketing objectives and meet the value requirements of its customers (e.g., Cravens and Piercy 2006; Varadarajan and Clark 1994). Marketing strategy is concerned with decisions relating to market segmentation and targeting, and the development of a positioning strategy based on 4Ps decision (e.g., Hunt and Morgan 1995). Based on the existing literature, theories, and practices, we define *strategic marketing* as *an organization's strategy that specifies its crucial choices pertaining to firm-level actions, customer-level actions, and market-level actions that helps the organization to create values for its customers and stakeholders*. *It deals with the strategic actions using the appropriate levels of methods to produce relevant and actionable insights*. Strategic contributions of marketing can be realized in terms of advancement in each of the sub-domain such as pricing, promotion, sales, etc. (e.g., Slater and Olson 2001). For example, marketing contributes to the strategic findings for a firm by showing an increase in profit with differentiated pricing strategy across heterogeneous product markets with undifferentiated advertising. After reviewing the extant literature (e.g., Slater and Olson 2001), we find a few distinct sub-areas and we briefly discuss the advances in these sub-areas below.

Product

Strategic contributions of marketing in the "product" area can be realized in multiple dimensions including product line extension, new product development and introduction (Fang et al. 2016b), and product lifecycle management. One of the most important product decisions is changes in the breadth of the product line. Should the product line be narrowly focused or should it be sufficiently broad to cover a set of complementary products, different performance specifications, or different price points (e.g., Putsis et al. 2001)? Related issues are the innovativeness of the products in the product line (e.g., Kerin et al. 1992), their relative customer-perceived quality (e.g., Jacobson and Aaker 1987). Other strategic contributions arising from domain of product management can be regarding product entry-exit (e.g., Green et al. 1995), product adoption (e.g., Manchanda et al. 2008), product cannibalization (Desai 2001), and overall product performance (Montoya-Weiss and Calantone 1994).

Pricing

Strategic contributions in the area of pricing include development of pricing strategy for existing as well as new products (Lal and Staelin 1984), minimizing price cannibalization, responding to competition (Rao and Bass 1985), etc. Fundamental contribution can tell us if a firm should charge a premium price. Premium prices may be justified based on innovativeness (e.g., Kerin et al. 1992), superior product or service quality (e.g., Jacobson and Aaker 1987), or brand equity (e.g., Keller and Aaker, 1992). Should a firm lower its prices during an economic downturn? Or should a firm maintain its price but emphasize on customer service during an economic slowdown? Pricing strategy can enhance the value of marketing for an industry (Kumar et al. 2014b). Contributions can be realized in forming forwarding looking pricing strategies (Nair 2007), market- and customer-based pricing strategies (e.g., Hinterhuber 2008; Hinterhuber 2004), and product/service-based pricing strategies (Iyengar et al. 2007).

Distribution and retailing

By realizing effective distribution and retailing strategies, a firm can enhance its market performance (Kumar et al. 2015b). The most common distribution decision is whether to use a selective or an intensive distribution system (Slater and Olson 2001). Other influential contributions in the domain of distribution lies in channel alignment (Kumar et al. 2015b), optimal shelf resource allocation strategies (Borin et al. 1994), multi-channel distribution (Wallace et al. 2004), and integration of the distribution (Johnson 1999).

Promotion

A firm can save a good amount of investment by designing effective promotional strategies. Strategic contributions of promotion lie in guiding the firms to develop effective promotional strategies (e.g., Kumar et al. 2015a), reduce media cannibalization (e.g., Naik et al. 2005), increase ROI on promotion, realize dynamic effect of promotion (Van Heerde et al. 2003), understand media synergy (Naik and Peters 2009), etc. Two dominant forms in promotion domain are advertising and personal selling. Advertising is particularly appropriate for creating awareness and interest, and for reaching a broader market. Personal selling is particularly appropriate when customers require more in-depth information in real time.

Branding

Firms always face issues with branding their products and services. Academic research has been contributing to firms branding decisions by showing largely the (1) do's and don'ts of branding, (2) valuation of a brand (Kamakura and Russell 1993), and (3) brand equity management (Aaker 1996; Yoo et al. 2000). Further, contributions can be understood in terms of how branding decisions are made across countries and customers, as well as product/service categories.

Social media and digital marketing

There has been a significant development in recent years in the area of social media and digital marketing. Contributions, in terms of design of digital and social media marketing strategies, can help a firm enhance its performance (Kumar et al. 2013; Ryan 2014). Significant development in the field of search engine optimization (Dou et al. 2010), social media analytics (De Vries et al. 2012; Hoffman and Fodor 2010), mobile marketing (Shankar and Balasubramanian 2009), and internet revolution (Varadarajan and Yadav 2002) can help a firm grow organically.

International marketing

When a firm needs to operate outside its home country, it has to follow the strategies, theories, and practices of international marketing. There has been enormous progress in the field of international marketing starting from whether or not firms should adopt a standardization strategy (Szymanski et al. 1993), or export venturing (Morgan et al. 2004), to the digitization of international marketing (Hamill 1997). Academic research can further enhance the contributions of international marketing by studying the country-specific differences, aligning global strategies to local strategies, and by appropriating customers' expectations in the international markets.

Customer-level strategy

There has been extraordinary growth in the customer-level strategy area (e.g., Palmatier et al. 2007). Starting from developing approaches to measure the lifetime value of a customer (Kumar et al. 2008) to modeling customers' forward-looking behavior (Erdem and Keane 1996), customer-level strategies have seen some critical developments. The use of scanner panel data and a firm's ability to track the behavior of a customer due to the improvements in technology are some of the antecedents of growth in this domain (Kumar 2013). As customers' preferences change with time, the economy, and changes in the lifecycle, a lot can be offered by academic research to bring strategic insights in this domain.

Firm-level strategy

Firm-level strategies (corporate and business level) are operationalized in terms of inter-industry and intra-industry variations. Firms' strategies on market research, targeting, segmentation, positioning, resource allocation, alliance, etc. can significantly influence firm performance. For example, market targeting strategy implies major commitments to satisfying the needs of particular customer groups through the development of specific capabilities (e.g., product, distribution, alliances) (Fang et al. 2016a) and investment (e.g., market research for understanding customers and competition) in dedicated resources (Corey 1991). These capabilities enable the organization to create a value proposition specific to the targeted segment utilizing the elements in the marketing mix (Slater and Olson 2001). There has been a significant development in terms of firm-level strategy research. Starting from market and entrepreneurial orientation (e.g., Jaworski and Kohli 1993; Merlo and Auh 2009) to marketing in the C-Suite (e.g., Germann et al. 2015; Nath and Mahajan 2011), academic research has been able to contribute to the growth of the firm-level strategy domain.

Services marketing strategy

Like product marketing, services marketing strategies have been discussed for decades (e.g., Berry 1995; Fisk et al. 1993; Zeithaml et al. 1985). The literature is able to provide insights on some critical questions such as "how does strategic marketing change in a service-based world?"(Lusch and Vargo 2014) or "how does relationship marketing work for services?" (Berry 1995). Strategic marketing research can further improve the contributions in the service domain by aligning customers' expectation to the service delivery, predicting the changing needs for services and tracking real time satisfaction of customers with the services.

Sales strategy

A sales strategy consists of a plan that positions a company's product/services or brands in a competitive status. Successful sales strategies help a firm to grow, assist sales people to focus on the target customers, and deliver values to those customers in a relevant, meaningful, and profitable way (e.g., Bagozzi 1978; Slater and Olson 2000; Weitz and Bradford 1999). Marketing scholars have done phenomenal work in elevating the contributions in the sales domain by exploring critical issues such as salesperson life time value (Kumar et al. 2014a), sales analytics (Skiera and Albers 1998), and salesforce management (Babakus et al. 1996; Cravens et al. 1993).

Innovation

"What should a firm do when it comes to innovation?" is a major question that every firm asks. Marketing studies have been successful in answering some of the critical questions such as (1) how does innovation create value for a firm? (Adner and Kapoor 2010); (2) should a firm participate in radical or incremental innovation? (e.g., Chandy and Tellis 2000; Chandy and Tellis 1998); (3) what is the dynamic impact of innovation? (Danneels 2002), etc. Further literature has been efficient enough to show if innovation is always beneficial to a firm. Strategic contributions also lie in explaining what a firm's approach should be for dealing with new product innovation (e.g., Grinstein 2008), innovation in the process and systems, and overall innovation management for the growth of the firm and for creation of customer value (e.g., Hashi and Stojčić 2013; O'Cass and Sok 2013).

Summary: contributions of the sub-areas

As explained above, each sub-area has contributed to strategic marketing research, which in turn, can help firms increase their performance. In the marketing literature, multiple studies show how rigor and relevance can be brought together to increase the contributions of strategic marketing research to business practices. For example, Natter et al. (2015) developed a pricing tool for "Entega" that reduced yearly sales cost for new customer business by 35%, on average, relative to previously used pricing heuristics. Kumar et al. (2008) showed that by modeling customer lifetime value (CLV) at IBM, the firm could generate more profits and a higher return on its investment. Social media can improve firm performance, and Kumar et al. (2013), by using a robust empirical methodology, proved that indeed social media management could help "Hokey-Pokey" to tap the market. Shankar et al. (2008) developed a multi-category brand equity model and showed how it influenced the performance of Allstate.

As we can see from the above discussion, there are multiple occasions where core strategy areas, and the empirical models used, could make strategic contributions. Now, it is worth understanding what types of models are able to facilitate such contributions across studies and across areas. We first look at all the studies under consideration and make a comprehensive list of the models used in those studies. The list of model types is created based on the authors' claim about the principal model, and the evaluation of the functional form they have employed to reflect on the core research questions of the study. We discuss all the major models used briefly in the following section.

Classification of models

Multivariate statistical models

The techniques that involve the simultaneous analysis of two or more variables are known as multivariate data techniques. They can be classified as interdependence or dependence techniques based on whether two or more variables have been designated as dependent on one or more independent variables. In the dependence technique, the value taken by the dependent variable can be predicted once the values of the independent variables are known. In the interdependence technique, concentration is on the interaction between variables. Here, variables are not classified as independent or dependent (Kumar 2015). The four interdependence techniques that are used most frequently in strategic marketing research are factor analysis, cluster analysis, conjoint analysis, and multidimensional scaling.

Mizik and Jacobson (2008) used a factor analysis model to examine the financial value impact of perceptual brand attributes. Green and Srinivasan (1990) showed how conjoint analysis can be beneficial for marketing research to generate strategic insights. Cluster analysis can be used for test market selection and can help a firm design effective market research strategies (Green et al. 1967; Punj and Stewart 1983). There are multiple avenues where multivariate statistical models are used to design effective marketing strategies (e.g., Baumgartner and Homburg 1996; Jedidi et al. 1997).

Panel data models

A panel data or longitudinal data model (Hsiao 2014) contains multidimensional data involving time series (e.g., weeks, months, year) observations over a number of cross-sections (e.g., households, firms, customers). Panel data has been widely employed in various studies in the domain of strategic marketing. For example, in the area of CRM, a transactional B2C panel data of a high-tech company was used to understand the customer selection and resource allocation strategies by using the Customer Lifetime Value Framework (e.g., Venkatesan and Kumar 2004); likewise, in the area of advertising, firm-level panel data was used to examine the impact of a firm's advertising and research and development (R&D) strategies on the systematic risk of its stock (e.g., McAlister et al. 2007). A wide application of panel data modeling can be seen in understanding customer heterogeneity (Chintagunta et al. 1991), designing loyalty programs (Sharp and Sharp 1997), and understanding market structure (Erdem 1996), among others.

Panel data brings out the inter-individual differences and intra-individual dynamics and therefore has several advantages over cross-sectional or time-series data. For example, it provides more accurate inference of model parameters because it contains more degrees of freedom and sample variability than cross-sectional data (Hsiao 2014). Panel data model allows researchers to control the impact of omitted variables (Hsiao 2014) and simplify the computation and statistical inference.

Choice models

In economics, discrete choice models describe, explain, and predict choices between two or more discrete alternatives such as buy/no buy in a purchase occasion, or choosing among transportation options. Choice models have been extensively used in multiple context including to understand consumer behavior (Kamakura et al. 2005), model household-level brand choice (Chintagunta et al. 2005), and understand brand credibility and consumer choice (Erdem and Swait 2004). Choice models are especially valuable to optimize marketing spend, determine optimal pricing strategy and product line, design effective promotional campaign, and predict market share.[1]

[1] https://www.decisionanalyst.com/whitepapers/choicemodelanalytics/.

Hazard models

The survival or hazard model can be used when the outcome variable of interest is duration, i.e., "the time until an event occurs." The event may be customer attrition, inter-purchase time, or failure of a machine (Kuruganti and Basu 2015). Hazard models are used to assess the risk or hazard of the termination of the relationship to check the likelihood that an event will occur given that the event has not occurred thus far (Chintagunta and Dong 2006).

Jain and Vilcassim (1991) used hazard models to study households' category purchase timing behavior in the context of the ground coffee category. The study decomposed the hazard into the baseline hazard, the effects of explanatory variables and the effects of unobserved heterogeneity. Hazard model has also been used to look into the issues of multiple dependent variables by using a bivariate hazard function (e.g., Chintagunta and Haldar 1998; Park and Fader 2004). Researchers have also combined the hazard model with a logit model in terms of studying purchase duration and brand choice behavior and a duration model with regression model looking into the effects of marketing activities on the joint purchase timing and expenditure decisions of households (Manchanda et al. 2006).

Cox's proportional hazard model tested the impact of a referral program and the value brought by the referred customers (e.g., Schmitt et al. 2011). Likewise, in the retailing context hazard modeling was used to examine the timing of customers' opt-in and opt-out decisions while accounting for their purchase behavior in a permission-based marketing context (Kumar et al. 2014c).

Linear regression models

Regression analysis is a statistical model for analyzing associative relationships between a dependent or criterion variable and a set of independent or predictor variables. There are five major uses of regression analysis—to determine whether the relationship exists, to assess the strength of the relationship, to uncover the structure and the form of the relationship, to predict the values of the dependent variables, and, finally, to control for the effects of other independent variables while evaluating the contributions of the focal variables (Aaker et al. 2016). It is concerned with the nature and degree of association between variables and does not imply any causality.

A well cited study by Reinartz and Kumar (2000) exercised the regression model to analyze the customer lifetime–profitability pattern in a non-contractual setting. The study was conducted on consumer-level transactional data recorded on a daily basis over a three-year window. Aaker and Keller (1990) investigated consumer evaluations of brand extensions by recording reactions to 20 brand extensions. Using linear regression, they found that potential negative associations can be neutralized more effectively by elaborating attributes of the brand extension and by reminding consumers of the positive associations with the original brand.

Non-linear models

Non-linear regression is characterized by the prediction equation, which depends nonlinearly on one or more unknown parameters (Smyth 2006). Non-linear regression usually arises when there are physical reasons to belief that the relationship between the response and the predictors follows a particular functional form.

Sood and Tellis (2005) used a non-linear regression model to study technological evolution and radical innovation for new technology products at the brand level in both B2B and B2C categories. They found that the results contradict the prediction of a single S-curve and technological evolution follow a step function, with sharp improvements in performance following long periods of no improvement. Further, non-linear models have been used in multiple context including diffusion (e.g., Venkatesan et al. 2004), retail competition (Dou and Ghose 2006), machine learning in direct marketing (Cui et al. 2006), and distribution (Lewis et al. 2006), among others.

Structural models

Structural models are typically based on optimizing behavior of agents (e.g., utility maximization by consumers, profit maximization by firms) (Chintagunta et al. 2006). In particular, this model of analysis is helpful to test "market and economic theories." Structural models can be static and/or dynamic. In marketing research, structural models are primarily used to understand competition (among firms in marketing mix elements such as pricing). Erdem and Keane (1996) applied dynamic structural modeling approach to understand the decision making under uncertainty by capturing the dynamic brand choice processes in consumer goods markets. Structural models have been extensively used to understand the competitive pricing behavior in the auto industry (Sudhir 2001).

Analytical models

Analytical modeling is a mathematical modeling technique used to explain and predict system behavior (Gokhale and Trivedi 1998). A mathematical model is a description of a system using mathematical concepts and language. It is a cost-effective technique compared to simulation and is considered a powerful and effective general purpose modeling tool (Trivedi 1982). Analytical models have been used in multiple occasions including to understand the decision making in marketing channels (Achrol and Stern 1988), competition (Eliashberg and Chatterjee 1985), and optimal advertising strategies (Dockner and Jørgensen 1988), to name a few.

Game-theoretic models

Game theoretic models pertain to the study of decision making in situations where two or more rational opponents are involved under conditions of competition and conflicting interest (Vohra 2007). The objective is to determine the rules of rational behavior in the game situations in which the outcomes are dependent on the actions of the interdependent players where each one has a set of available strategies. In game theory, the Nash equilibrium is a solution concept of a non-cooperative game involving two or more players in which each player is assumed to know the equilibrium strategies of the other players, and no player has anything to gain by changing only his or her own strategy.

Game theoretic models are widely popular in marketing research. Starting from the understanding of channel power (Kadiyali et al. 2000), advertising game (e.g., Naik et al. 2005) and structure of strategic alliance (Parkhe 1993), game theoretic models have been helpful to extend our understanding on strategic implications of marketing.

Structural equation models

Structural equation models (SEM) refer to a diverse set of mathematical models, algorithms, and statistical models that fit networks to construct data. SEM incorporates factor analysis, partial least square, latent growth modeling, as well as path analysis. In other words, it first validates the measurement model through confirmatory factor analysis (CFA) and then fits the structural model through path analysis. This technique serves purposes similar to multiple regressions but is more powerful in prediction. It takes into account the interaction and non-linearity of correlated independent variables having multiple indicators and one or more latent dependent variables, which in turn, may also have multiple indicators. With the use of multiple items to represent latent variables, it leads to more accurate estimates of cause and effect relations among constructs (Kumar and Pansari 2016).

SEM is a popular model in marketing research and has been used extensively in understanding marketing strategy–performance link (Cavusgil and Zou 1994), brands' spillover effect (Simonin and Ruth 1998), and customer behavior (Baumgartner and Homburg 1996), to name a few.

Dynamic models

A dynamic model represents the behavior of an object over time. It is used where the object's behavior is best described as a set of states that occur in a defined sequence. Dynamic models have been extensively used to derive strategic insights in marketing literature. Specifically, dynamic models see their importance in understanding the dynamic effect of social influence on product adoption (Risselada et al. 2014), market entry-exit (Aguirregabiria and Suzuki 2014), and compensation systems (Chung et al. 2013), to name a few.

Event studies

Event study is a statistical method that is used to assess the impact of an event on the value of a firm. For example, an event study can tell us how a firm's merger and acquisition decisions influence its performance. Stock price, according to modern financial portfolio theories, takes into account all available information and expectations about the future. Based on this understanding, it is possible to analyze the effect of a specific event on a company by looking at the associated impact on the firm's stock. Event study methodology has been used in many occasions. For example, Agrawal and Kamakura (1995) used event study approach to understand the effect of celebrity endorsers; Chen et al. (2009) used event study to check how product recall strategies influence a firm's financial values; and Swaminathan and Moorman (2009) studied 230 announcements to understand marketing alliances, firm networks, and firms' value creation potential.

Field/natural experiments

A natural experiment is an approach in which individuals or a group of individuals are exposed to experimental and controlled conditions. Processes governing the exposures arguably resemble random assignments. Field experiments are done in a real-life setting where experimenters still manipulate the independent variables (Petersen et al. 2015). Natural experiments have been used in marketing literature extensively (e.g., Neslin and Shoemaker 1983). However, recent trends in the use of natural experiments is in the social media stage (e.g., Chen et al. 2011). Similarly, field experiments are also extensively used in the marketing literature. Starting from shelf management (Dreze et al. 1995) to understanding the role of CSR in strengthening multiple stakeholder relationships (Sen et al. 2006), field experiments are immensely helpful to derive strategic insights.

Count data models

Count data is a type of data in which observations can take only non-negative integer values, and these integers arise from counting rather than ranking. Generally, Poisson regression is used to model count data. Count data models have been used extensively in CRM, new product forecast (Neelamegham and Chintagunta 1999), segmentation in sales response (Bucklin et al. 1998), and sales promotion (Gupta 1988), to name a few. These models have a number of advantages over an ordinary linear regression model, including a skew, discrete distribution, and the restriction of predicted values to non-negative numbers.

State-space models

State-space model is a mathematical representation of a physical system that shows a set of input, output, and state variables related by some form of differential equations. It refers to a class of probabilistic graphical models that describe the probabilistic dependence between a set of latent state variables and an observed measurement (Koller and Friedman 2009). The model can be represented as either continuous-time or discrete-time. State-space models reduce the cost of computation (Rossi and Allenby 2003). In marketing, few studies have adopted state-space modeling in the platform of media planning (Naik et al. 2005), customer purchase behavior (Gönül and Srinivasan 1996), and brand switching behavior (Vilcassim and Jain 1991), to name a few.

Time series models

Time series models are used to analyze time series data in order to extract meaningful statistics. Time series analysis may be divided into two classes: frequency-domain models and time-domain models. Few approaches that are prominent in management research (marketing, finance, strategy) are auto-correlation analysis, cross-correlation analysis, spectral analysis and wavelet analysis. Time series models are extensively used in strategic marketing research. Models such as vector auto-regressive (VAR), ARIMA, etc. are widely used in strategic marketing research. Specifically, time series models are found to be useful to model market response (Hanssens et al. 2003), understand shelf space allocation decisions (Achrol 2012), understand the impact of traditional marketing and online consumer activity determining path to purchase (Srinivasan et al. 2015), and impact of advertising (Xiong and Bharadwaj 2013), to name a few.

Learning models

The base of a learning model is the traditional discrete choice models. Researchers have developed learning models by postulating that consumers have incomplete information about product attributes and that they learn about the attributes of the product and integrating this understanding with some form of choice models (Ching et al. 2013). Learning models are mainly used to understand a consumer's decision-making process (e.g., Erdem and Keane 1996; Shin et al. 2012; Zhao et al. 2013; Zhao et al. 2011).

Spatial models

Spatial models allow cross-sectional and longitudinal correlations among responses to be explicitly modeled by locating entities on some type of map. This type of model can capture a wide variety of effects, including spatial lag, spatial drift and spatial autocorrelation that influenced firms' or consumers' decision making (Bradlow et al. 2005). In the marketing literature, spatial models are widely used especially in the domain of product diffusion (Kumar and Krishnan 2002), and in the understanding of geographical markets for firms (Jank and Kannan 2005). Spatial models help to understand geographical/spatial competition among firms, develop a competitive network for better firm performance, and design effective distribution and channel strategies.

Non-parametric models

Non-parametric models are a category of models in which the predictor does not take a predetermined form but is constructed according to the information derived from the data. This type of model generally requires more data points than the parametric models as data must give the model structure and provide estimates. Although non-parametric models are not very common in strategic marketing literature, a few studies have used them in the context of impact of direct marketing (Bult 1993), consumers' choice (Farias et al. 2013), and customer lifetime value management (Donkers et al. 2007). Non-parametric models avoid the curse of dimensionality.

Empirical context

Data

Based on the above discussion, it is evident that different strategy areas and models contribute to strategic marketing research and have been able to generate impact. However, it is important to understand which areas had a relatively greater/lesser impact; and which models, journal types, and estimation approaches moderated the relationship between strategy areas and strategic findings. In order to find the relative impact of different areas and moderating roles of models, journal types, and estimation approaches in generating strategic insights, we need relevant data. We adopted an intensive data collection approach. Based on the major sub-domains as discussed earlier, we searched for the keywords (e.g., "pricing," "international marketing"). We first collect all the articles containing the relevant keywords. We searched mainly in Google Scholar, ABI, and EBSCO. Based on this search, we find 1121 articles (published since 1960). From this sample, we considered articles published in major marketing journals as our focus is on "strategic contributions of marketing." Therefore, we considered articles published in major journals including *Journal of Marketing* (JM), *Journal of Marketing Research* (JMR), *Management Science* (MANSC), *Journal of the Academy of Marketing Science* (JAMS), *Marketing Science* (MKSC), *International Journal of Research in Marketing* (IJRM), *Journal of Consumer Research* (JCR), and *Journal of Retailing* (JR). In order to ensure that the selected studies fall within the topical domain of strategic marketing (that answers the question "what constitutes a strategic marketing study?"), we used four criteria: (1) the article should have at least one strategic contribution (two authors separately judge this after subjective evaluation of the contributions of the study); (2) the article should have some relation with strategic marketing research (e.g., we opt-out of a study that discusses operational efficiency of the firm due to market growth and reduction in unemployment); (3) the article's authors should claim that the study advances the understanding of some aspects of strategic marketing research; and (4) the article should be published in a journal that is considered a top-tier journal in many parts of the world (e.g., IJRM is considered a top-tier journal in Europe). Further, we also removed all the conceptual studies and studies where no statistical/econometric approaches were used. Given these restrictions, we arrived at 485 articles to be used for the analysis.[2]

To understand the potential link between core strategy areas, models, and their respective strategic contributions, every article was coded on a variety of critical dimensions such as central research area, estimation approach, types of journal, data source, market setting, nature of the study, age of the article, and the models used.

Focal research areas In the beginning, articles were categorized on the basis of their *focal strategy research area* (e.g., customer-firm, sales, pricing, distribution and retailing, social media, product, international marketing, branding, innovation), and each of the areas was coded as 0 for "no" or 1 for "yes." For example, if the main focus of the study was on pricing, we coded 1 for the pricing variable and 0 for other areas.

Focal research models We coded the studies based on the focal model used. Now, a study can use more than one model at a time. In such context, we looked for the *principal* model used to solve the focal research questions. For example, studies in the customer strategy domain used "Tobit model." Tobit model is a form of choice model, although a regression model is used if the model is estimated in two steps (type II Tobit). Further, in a type III Tobit, count data model is also used along with choice and linear models. For those studies, we coded 1 for choice model, and 0 otherwise. Consistently, we coded all

[2] The list of articles can be provided upon request.

the studies for the models they used. We made sure that each study was coded for the focal model used such that we have a dummy variable coding for each model.

Journal type We coded the articles based on the journal in which they were published. For example, if the article is published in *Journal of Marketing*, we coded 1 for JM and 0 for the rest of the journals. Similar coding was used for each of the other journals included in this study.

Market setting It is important to realize that studies conducted in B2B settings are different from that of a B2C setting in terms of strategic contributions as well as model selection. Hence, articles were further categorized according to their selection of market setting—B2B, B2C, and both (some studies are conducted in both the markets). We also note that some articles do not explicitly discuss the market setting. Accordingly, we created dummy variable coding for B2B (coded 1 if study is in B2B market, and 0, otherwise), B2C, both, and no category.

Source of data Contributions of a strategy area or a modeling approach may be dependent on the availability of the data. In this context, we looked for the source of the data that is used by the articles. We found three main data sources—primary, secondary and commercial. However, a large number of studies do not explicitly mention the sources. We create variables accordingly: primary (if the data source is primary), secondary (if the data source is secondary), commercial (if the data source is commercial-data purchased from third party sources), mixed (if the study uses data from multiple sources), and no source (if the data source is not mentioned in the study). Further, we combine commercial, mixed, and no source as "other sources" due to data limitations.

Unit of analysis of the study Unit of analysis of an article may influence the performance of the article. After reading the articles, we found that the unit of analysis can be at: firm, customer, store, brand, product, and individual (such as sales person, managers, etc.) level. We also found that there are a large number of articles where unit of analysis is not explicitly mentioned. We categorized unit of analysis as firm level, customer level, brand level, product level, store level, individual level, and no mention (each variable was coded as a dummy variable). As most of the analysis are done at customer and firm level (see Table 1), we combined brand level, product level, store level, individual level, and no mention as "other unit of analysis." We used "customer-level analysis" and "firm-level analysis" in our models.

Nature of the study After reading through the articles, we also felt that the "nature" of the study may influence the contributions of the study to the literature. For example, an empirical study may shed better light on a specific issue than that of an experiment-driven article. Generally, the nature of a study can be any of the following: empirical, conceptual, and/or review. We excluded review and conceptual studies from our study. However, the impact of an article can be different based on whether the article uses empirical data (e.g., transaction data, commercial data), experimental data, survey-based data, or data from meta-analysis. Hence, our classification of the nature of the study is granular and is solely driven by the nature of data used in the study. We could categorize an article's primary nature to be empirical, experimental, survey, mixed (e.g., if study has both experimental and empirical), meta-analysis, analytical, and other type (e.g., neural network). We coded each of them as a dummy variable (e.g., if study is empirical in nature, we coded empirical as 1, and 0, otherwise). As evident in Table 1, more than 46% of the articles are of empirical in nature. Due to lack of sufficient observations, we combined experimental, survey, 'mixed (e.g., if study has both experimental and empirical), meta-analysis, analytical, and other type. We defined the nature of the article as empirical or non-empirical (coded 1 if study is empirical in nature, and 0, otherwise).

Age of the article We also captured the age of the articles under consideration. We computed the age as the difference between 2016 and the year of publication of each of the articles.

Estimation approaches In addition to the model type, we examined the linkage between different estimation approaches to the contributions and the performance of the article (in terms of citations). Therefore, different estimation approaches were explored and coded (0 for "no" or 1 for "'yes"): Maximum Likelihood Estimation (e.g., if the estimation approach is MLE then 1, else 0), Generalized Methods of Moments (GMM), Bayesian, Ordinary Least Square (OLS), Normal (such as VAR, time series), and continuous-discrete choice estimation.

Article impact—citations and number of strategic contributions We collected data to check the impact of an article. In this context, we collected information about citations of each article under consideration.[3] We have the citation information from Google Scholar and Web of Science. Further, we read through each article and noted down the number of strategic contributions offered by each article as claimed by the authors. In order to do this, we read through the sections such as "discussion," "strategic contributions," and "conclusion" across different articles. For example, a study by Chen et al. (2009) published in *Journal of Marketing* discusses the strategic contributions of the study in the section "General Discussion." They write: "A key finding in this research

[3] As of November 11, 2016.

Table 1 Frequency distribution

Data	Frequency	Average # strategic contributions per article	Average # Google Scholar citations per article	Average # Web of Science citations per article
Journal Type				
Journal of Marketing (JM)	139	2.72	781.06	180.35
Journal of Marketing Research (JMR)	85	2.34	455.62	122.98
Journal of Academy of Marketing Science (JAMS)	54	2.55	194.84	33.91
Marketing Science (MKSC)	71	2.01	209	55.94
Management Science (MANSC)	65	1.82	279.53	85.55
Journal of Retailing (JR)	49	2.31	339.51	69.84
International Journal of Research in Marketing (IJRM)	22	2.63	284.86	40.68
Core Strategy Area				
Customer	86	2.71	698.6	144.26
Brand	20	2.15	417.55	95.1
Distribution	47	2.19	300.69	62.74
Product	79	2.26	42.3.06	129.49
Price	55	1.76	232.58	63.49
Promotion	27	2.15	216.04	60.19
Firm	46	2.7	378.78	94
International Marketing	5	2.8	712.2	223.6
Sales	71	2.18	354	79.8
Social Media	34	2.65	409.76	102.23
Services	5	2.8	3125.2	559
Innovation	10	3.8	381.2	127.6
Nature of the study				
Empirical	231	2.65	432.16	102.07
Experimental	46	2.28	543.28	121.58
Survey	81	2.54	681.23	158.03
Mixed	21	2.57	410.33	98.76
Meta-Analysis	10	1.8	565.6	138.4
Analytical	95	1.59	201.87	59.76
Other type	1	2	647	152
Level of Analysis				
Firm-level	236	2.3	334.74	91.88
Customer-level	128	2.52	655.7	133.33
Store-level	8	2.75	289.88	87.375
Brand-level	14	2.5	745.78	160.14
Product level	29	1.97	362.59	108.41
Individual level	64	2.42	386.23	89.61
No unit	6	2.33	529.84	114.83
Types of Market				
B2B	41	2.66	686.39	154.51
B2C	232	2.53	484.12	110.42
BOTH	18	3.22	390.27	120.55
No Category	194	2.03	343.38	88.33
Sources of Data				
Primary	243	2.51	549.33	124.78
Secondary	95	2.69	394.87	106.08
Commercial	16	2.31	334.81	101.25
No Source	115	1.66	290.97	71.30
Mixed	16	3.375	267.43	65.06
Types of Models				
Multivariate statistical method	38	2.07	420.89	109.01
Linear Regression model	107	2.63	583.15	134.74
Panel data model	20	2.7	295.7	70.6
Choice	25	2.6	309.64	85.28
Hazard	8	3.12	98.75	28.62
Non-linear	7	3.43	492.29	150.57
Non-parametric	4	2.25	211.75	47.25
Time-series	12	2.75	248	61.33
Count-data	1	4	445	157

Table 1 (continued)

Data	Frequency	Average # strategic contributions per article	Average # Google Scholar citations per article	Average # Web of Science citations per article
Structural models	10	2.1	294.6	88.2
Learning models	4	2.75	204.75	52.5
Spatial Models	2	3	188.5	50.5
Dynamic Models	15	2.27	359.27	87.14
State-space models	1	1	125	0
Analytical Models	86	1.57	222.29	64.27
Game-theoretic	12	2.08	200.08	70.17
Event-study	10	2.9	271.4	72.5
Field/Natural-experiment	11	2.27	389.36	89.63
Structural Equation Models	95	2.61	656.96	142.08
Other Model	17	2.23	762.76	159.29
Types of Estimation Approach				
GMM	8	3.125	260.75	68.25
BAYESIAN	17	2.47	158.88	48.05
OLS	148	2.73	566.99	127.39
MLE	149	2.51	458.35	109.35
No Estimation	155	1.83	354.05	91.05
other	8	2.25	278.125	79.25

is…. We also find that less reputable firms….” In this context, we counted “number of strategic contributions” as 2, since the article claims to make two key contributions. We provide the frequency distribution of the variables (see Table 1) as well as the average number of citations (Google Scholar and Web of Science) per article and the average number of strategic contributions per article used in the study in order to discuss the operationalization in the next section.

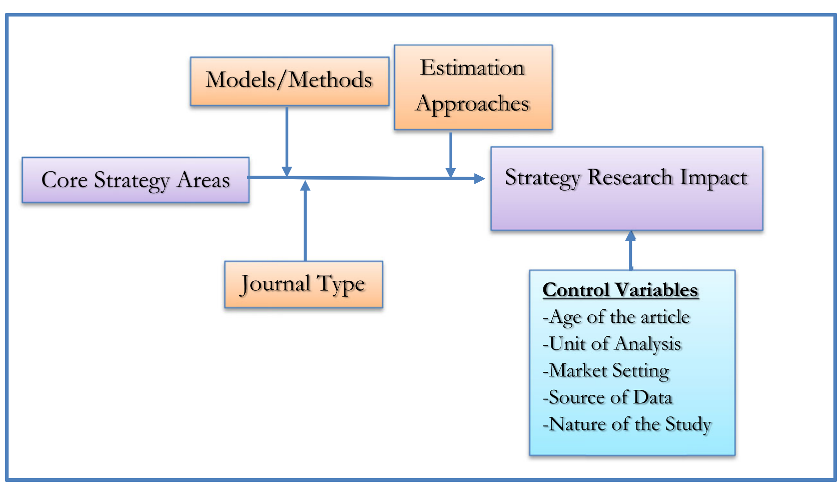
We develop an organizing framework (see Fig. 1) based on the available data in order to study the impact of core areas, and the moderation effect of models, journal types, and estimation approaches on the impact of strategic marketing research.

Variable operationalization

Dependent variables We used three different dependent variables in this study. For the primary analysis, we used “citations of the study” as the dependent variable. In this context, we tested our models with the Google Scholar citation index. For the additional robustness analysis, we used the “number of strategic contributions,” and “Web of Science citation” of the article as the dependent variables.

Independent variables Independent variables for the study are the focal research areas of the articles. As shown in Table 1, for some of the areas, the number of studies is not large enough to create a unique variable. For the simplicity of the analysis as well as due to data limitation, we combined the focal research areas of the studies as follows. We operationalized the variable “4Ps strategy” if the article is from any of the sub-areas: product, price, promotion, and distribution/retailing. We coded 4Ps strategy as a dummy variable. The variable “sales strategy” was coded as 1 if the article’s focal research area is “sales,” and 0, otherwise. We coded “customer-level strategy” as 1 if the

Fig. 1 An organizing framework for assessing the impact of strategic marketing research



article's focal research area is "customer" and 0 if others. Finally, we coded "other strategy" as 1 if the article's focus is any of the following: social media, firm, international marketing, branding, services, innovation, and 0 otherwise. We used n-1 dummy variables (e.g., 3 strategy research areas) for analysis with one of the strategy areas as the baseline.

Moderating variables We tested the moderating impact of three sets of variables in three different settings. We tested for the moderating impact of the models used. Specifically, we tested for the moderating influence of linear regression models, multivariate analysis, structural equation models, analytical models, and other models by coding each of them as a dummy variable. For example, we coded the "other model" as 1 if the model used is from any of the following explicitly: panel data, choice model, structural model, time series analysis, hazard model, state-space model, learning model, event study approach, natural/field experiments, non-parametric models, spatial models, count data models, non-linear models, dynamic models, and game-theoretic models. We created the variable "other models" as there were not enough data points for each of the above models to create a unique variable. We also tested for the moderating roles of journal type. We categorize journals as strategy-focused journals and quant-focused journals. We grouped JM, JMR, and JAMS as strategy-focused, and MKSC, MANSC, JR, and IJRM as quant-focused journals.[4] We coded strategy-focused journals as 1 if the article is published in any of the journals: JM, JMR, or JAMS, otherwise 0. We had three studies from the *Journal of Consumer Research* (JCR). Since JCR cannot be defined either as a strategy or quant-focused journal, we removed these three articles from our data. Further, we also tested for the moderating role of the estimation approach. We coded complex estimation as 1 if the estimation approach is not ordinary least squares, otherwise else 0.

Control variables We controlled for several other variables in our study including the "nature" of the study. We accounted for the source of the data. We created three dummy variables to account for the data source: primary data source, secondary data source, and other. We used primary and secondary data sources, with the "other" as the baseline in our analysis. It is critical to account for the unit of analysis as it can have a significant effect on the citations. We accounted for the unit of analysis by including firm-level analysis and customer-level analysis as two additional control variables. We also controlled for the market setting. If the context is in B2C, we coded "market" as 1, otherwise 0. Finally, the age of an article can impact its citation. We controlled for the age of the study accordingly.

[4] We arrive at this conclusion based on two criteria: (1) after considering comments from the Editors of different journals in conferences/doctoral consortia and (2) after carefully evaluating the articles published in these journals.

Model development

We estimated three different models in three different settings in our study in order to generate different insights.

Setting 1: moderating roles of different models In this setting, we try to understand the impact of focal strategy research areas on the article's citations and try to explore the moderating role of models used in such relationships. We controlled for the journal type and estimation approaches and other variables in our model. We evaluated several functional forms including a linear and a log-linear model. For example, the basic model with log of Google Scholar citations as the dependent variable that we estimated is as follows:

$$\begin{aligned}\log(1+Citation_i) = {} & \beta_0+\beta_1 cust_i+\beta_2 other\_area_i \\ & +\beta_3 sales_i+\beta_4 linear_i+\beta_5 multi_i \\ & +\beta_6 analytical_i+\beta_7 SEM_i \\ & +\beta_8 cust_i\times linear_i+\beta_9 cust_i \\ & \times multi_i+\beta_{10} cust_i\times analytical_i \\ & +\beta_{11} cust_i\times SEM_i \\ & +\beta_{12} other\_area_i\times linear_i \\ & +\beta_{13} other\_area_i\times multi_i \\ & +\beta_{14} other\_area_i\times analytical_i \\ & +\beta_{15} other\_area_i\times SEM_i \\ & +\beta_{16} sales_i\times linear_i+\beta_{17} sales_i \\ & \times multi_i+\beta_{18} sales_i\times analytical_i \\ & +\beta_{19} sales_i\times SEM_i \\ & +\beta_{20j} control\_variables_{ij}+\epsilon_{i1} \qquad (1)\end{aligned}$$

Where,

$cust_i$	if the article i focuses on customer-level strategy
$other\_area_i$	if the article i focuses on other area strategy
$sales_i$	if the article i focuses on sales strategy
$linear_i$	if the article i uses linear models
$multi_i$	if the article i uses multivariate models
$analytical_i$	if the article i uses analytical models
SEM_i	if the article i uses SEM

$control\_variable_{ij}$	jth control variable for ith study
$Citation_i$	Google Scholar citation for study i

For Eq. 1, we used "4Ps strategy" as the baseline for strategy and "other model" as the baseline for modeling approach.

Setting 2: moderating role of estimation approaches In this setting, we try to understand the impact of focal strategy areas of research on the article's citations and explore the moderating role of estimation approaches used in such relationships. The model that we estimated here is as follows:

$$\begin{aligned}\log(1+Citation_i) = {} & \beta_0+\beta_1 customer_i+\beta_2 sales_i \\ & +\beta_3 other\_areas_i \\ & +\beta_4 complex\_estimation_i \\ & +\beta_5 customer_i \\ & \times complex\_estimation_i+\beta_6 sales_i \\ & \times complex\_estimation_i \\ & +\beta_7 otherareas_i \\ & \times complex\_estimation_i \\ & +\beta_{8j} control\_variables_{ij}+\epsilon_{i2}\end{aligned} \tag{2}$$

For Eq. 2, we considered 4Ps strategy ($4Ps_i$) as the baseline for comparison.

Setting 3: moderating role of journal type Finally, we tested for the moderating impact of journal type (strategy-focused journal vs. quant-focused journal) on the relationship between focal areas of study and the citations of the study.

$$\begin{aligned}\log(1+Citation_i) = {} & \beta_0+\beta_1 customer_i+\beta_2 sales_i \\ & +\beta_3 other\_areas_i \\ & +\beta_4 strategy\_focused\_journal_i \\ & +\beta_5 Customer_i \\ & \times strategy\_focused\_journal_i \\ & +\beta_6 sales_i \\ & \times strategy\_focused\_journal_i \\ & +\beta_7 other\_areas_i \\ & \times strategy\_focused\_journal_i \\ & +\beta_{8j} control\_variables_{ij}+\epsilon_{i3}\end{aligned} \tag{3}$$

For Eq. 3, we considered 4Ps strategy ($4Ps_i$) as the baseline for comparison.

Results

We estimated Eqs. 1–3 using an ordinary least square (OLS) estimation approach. We tested the residuals of the models for any violation of the assumptions, and corrected for any biases and inefficiencies in parameter estimates, when necessary. The correlation and descriptive statistics of the variables used are shown in Table 2.

We discuss below the results of the three different settings.

Setting 1 results

Main effects For Eq. 1, using log of Google Scholar citations as the dependent variable (see Table 3), we found that "sales" strategy ($\beta = -0.35, p < 0.1$) had a significantly lower effect on citations than the 4Ps areas. However, results show that customer ($\beta = 0.34, p < 0.1,$), and other strategy areas($\beta = 0.3, p < 0.1$), had a significant positive impact on citations with respect to the 4Ps area. Regarding the direct effects of the models, we found that linear models ($\beta = 0.3, p < 0.1$), multivariate analysis ($\beta = 0.55, p < 0.05$), and SEM ($\beta = 0.68, p < 0.01$) had a significantly greater impact on generating strategic insights, measured in terms of citations, than other models. Analytical models($\beta = 0.09, n.s.$) did not have a significant impact on citations. In this setting, we did not find the significant direct effect of the 'estimation approach' ($\beta = 0.11, n.s.$) and strategy-focused journal ($\beta = 0.002, n.s.$) on citations.

Moderating effects In the domain of strategic research focusing on "customer", linear models ($\beta = 0.602, p < 0.1$) and structural equation models ($\beta = 0.79, p < 0.05$) had a significantly greater impact on citations than other models. While multivariate analysis($\beta = -0.69, n.s.$) did not have a significant impact, we found that analytical models ($\beta = -0.77, p < 0.1$) negatively moderated the relationship between strategic research focusing on "customer" and citations. When an article's focus was on "other areas" and the article used SEM ($\beta = 0.54, p < 0.1$), the same article was able to generate more impact than an article using other models. However, in "other area," the moderating impact of linear($\beta = 0.17, n.s.$), analytical ($\beta = 0.277, n.s.$), as well as multivariate analysis($\beta = -0.15, n.s.$) was not significant with respect to other models. Results further show that linear models($\beta = -0.67, p < 0.1$), analytical models($\beta = -0.75, p < 0.1$), and multivariate analysis ($\beta = -0.97, p < 0.05$) used in the strategic research focusing on "sales" generated relatively lesser citations than an article using other models in the sales strategy domain.

Table 2 Correlation and descriptive statistics

	Citation	MULTI	LINEAR	SEM	ANA	OTHER	CUST	4P	SALES	OTS	CEST	STJ	PRI	SEC	FIRM	CUS	EMP	MKT	AGE
Citation	1																		
Multivariate Analysis (MULTI)	0.006	1																	
Linear Regression Models (LINEAR)	0.09**	-0.15***	1																
SEM	0.1*	-0.14***	-0.26***	1															
Analytical Models (ANA)	-0.11**	-0.13***	-0.24***	-0.22***	1														
Other Models (OTHER)	-0.11**	-0.18***	-0.34***	-0.31***	-0.29***	1													
Customer-level strategy (CUST)	0.11**	-0.01	-0.01	0.002	-0.08*	0.11**	1												
4Ps strategy (4P)	-0.09**	-0.03	0.02	-0.21***	0.26***	-0.04	-0.4***	1											
Sales Strategy (SALES)	-0.06	0.05	-0.06	0.36***	-0.05	-0.22***	-0.19**	-0.35***	1										
Other Strategy (OTS)	0.06***	0.01	0.04	-0.05	-0.17***	0.13***	-0.26***	-0.4***	-0.2***	1									
Complex Estimation (CEST)	-0.08*	0.16***	-0.5***	0.03	0.29***	0.12**	0.08*	-0.02	-0.05	-0.003	1								
Strategy-Focused Journal (STJ)	0.2***	0.03	0.15***	0.27***	-0.43***	-0.01	0.09**	-0.25***	0.15***	0.07*	-0.31***	1							
Primary data source (PRI)	0.11**	0.21***	0.06	0.38***	-0.38***	-0.2***	0.05	-0.24***	0.3***	-0.02	-0.13***	0.28***	1						
Secondary data source (SEC)	0.001	-0.08*	0.1**	-0.17***	-0.17***	0.27***	0.07	-0.02	-0.2***	0.13***	-0.12**	0.09**	-0.19***	1					
Firm-level analysis (FIRM)	-0.08*	-0.17***	-0.03	-0.17***	0.29***	0.05	-0.2***	0.23***	-0.2***	0.09**	0.03	-0.13***	-0.37***	0.08*	1				
Consumer level analysis (CUS)	0.1**	0.08*	0.06	-0.05	-0.2***	0.09**	0.45***	-0.23***	-0.19***	0.02	0.02	0.01	0.21***	-0.02	-0.58***	1			
Nature of the study	-0.02	-0.01**	0.14**	-0.18***	-0.32***	0.34***	0.17***	-0.13***	−0.16***	0.14**	-0.12**	0.17***	-0.09**	0.38***	0.029	0.05	1		
Market (MKT)	0.02	0.01	0.05	-0.004	-0.2***	0.16***	0.19***	-0.09**	0.02	-0.08*	-0.09**	0.09**	0.21***	0.06	-0.28***	0.3***	0.1**	1	
Age (AGE)	0.13***	0.09**	-0.02	-0.007	0.18***	-0.19***	-0.18***	0.25***	0.18***	-0.27***	0.01	0.01	0.004	-0.14***	0.003	-0.15***	-0.26***	0.03	1
Mean	105.69	0.07	0.22	0.19	0.17	0.29	0.17	0.42	0.14	0.24	0.69	0.57	0.5	0.19	0.48	0.26	0.47	0.47	15.64
Variance	164.15	0.26	0.41	0.39	0.38	0.45	0.38	0.49	0.35	0.43	0.46	0.49	0.5	0.39	0.5	0.44	0.49	0.5	10.35

***significant at 1%|**significant at 5%|*significant at 10%

Table 3 Results

	Setting 1		Setting 2		Setting 3	
	Equation 1		Equation 2		Equation 3	
	Estimates	Std. Error	Estimates	Std. Error	Estimates	Std. Error
Intercept	5.15***	0.07	3.68***	0.13	3.45***	0.11
Main effects—Models						
Linear Regression Models (LINEAR)	0.3*	0.18				
Multivariate Analysis (MULTI)	0.55**	0.26				
Analytical Model (ANALYTICAL)	0.09	0.19				
Structural Eq. Models (SEM)	0.68***	0.2				
Main effects—Strategy Areas						
Customer-level strategy (CUST)	0.34*	0.2	0.32*	0.13	0.62*	0.34
4Ps strategy (4P)						
Other Strategy (OTS)	0.3*	0.15	0.18	0.19	0.07	0.17
Sales Strategy (SALES)	-0.35*	0.201	-0.48*	0.25	-0.09	0.2
Main effect—Estimation Approach						
Complex Estimation (CEST)	0.11	0.14	-0.07	0.19		
Main effect—Journal						
Strategy-Focused Journal (STJ)	0.002	0.13			0.45***	0.15
Moderating effects						
CUST*LINEAR	0.602*	0.35				
CUST*MULTI	-0.69	0.55				
CUST*ANALYTICAL	-0.77*	0.44				
CUST*SEM	0.79**	0.36				
OTS*LINEAR	0.17	0.25				
OTS *MULTI	-0.15	0.43				
OTS *ANALYTICAL	0.277	0.55				
OTS *SEM	0.54*	0.31				
SALES*LINEAR	-0.67*	0.4				
SALES*MULTI	-0.97**	0.47				
SALES*ANALYTICAL	-0.75*	0.42				
SALES*SEM	-0.28	0.23				
CUSTOMER*CEST			0.44*	0.24		
SALES*CEST			-0.51*	0.28		
OTS*CEST			0.38*	0.23		
CUSTOMER*STJ					-0.14	0.37
SALES*STJ					-1.09***	0.28
OTS*STJ					0.46**	0.21
Control effects						
Primary data source	0.47***	0.14	0.85***	0.19	0.68***	0.19
Secondary data source	0.42**	0.17	0.57**	0.23	0.43*	0.23
Firm-level analysis	-0.03	0.15	0.06	0.2	0.008	0.2
Consumer level analysis	-0.11	0.19	-0.27	0.24	-0.24	0.24
Nature of the study (empirical = 1)	-0.19	0.12	-0.39**	0.16	-0.42**	0.16
Market (B2C = 1)	0.12	0.12	0.03	0.15	0.13	0.16
Age of the study	0.05***	0.005	0.033***	0.007	0.031***	0.007
Model Performance						
R Square	0.223		0.2021		0.11	

***significant at 1%|**significant at 5%|*significant at 10%

Control effects We also found the significant effect of "age of the article" ($\beta = 0.05, p < 0.01$) on the citations. In addition, our results show that data source mattered. Primary ($\beta = 0.47$, $p < 0.01$) and secondary ($\beta = 0.42, p < 0.05$) data sources used in an article generated higher citations than other data sources. We did not find any significant effect of firm and customer-level analysis, nature of the study, and market setting in this context.

Setting 2 results

Main effects In Eq. 2, we tried to understand how the estimation approach used in an article moderates the relationship of the focal strategy area of the article and the citation. While we found that complex estimation approach did not have a significant impact ($\beta = -0.07, n.s.$) on citations, we did find that in this context, the impact of sales area ($\beta = -0.48$,

$p < 0.1$) was relatively lower on citations than the 4Ps strategy area. Further, customer strategy area ($\beta = 0.32, p < 0.1$) had a relatively higher impact on citations than 4Ps area.

Moderating effects Complex estimation approach ($\beta = -0.51, p < 0.1$) used in the strategic research focusing on "sales" had a significantly lower impact on citations than complex estimation approach used in 4Ps strategy area. We also found that if an article embedded complex estimation approach and the article was focused on customer area($\beta = 0.44, p < 0.1$), or other areas($\beta = 0.38, p < 0.1$), it had a relatively greater impact on citations than the article using complex estimation in the 4Ps strategy area.

Control effect We found that if the data source used in the study was either primary ($\beta = 0.85, p < 0.01$), or secondary ($\beta = 0.57, p < 0.05$), it had a greater impact on the citation than other sources. Further, age of the article ($\beta = 0.033, p < 0.01$) contributed positively to the citations of the study. Finally, if the article was empirical in nature ($\beta = -0.39, p < 0.05$), it had a relatively lower impact on citation than a non-empirical article. In this context, we did not find any significant impact of firm- and customer-level analysis, nor market setting.

Setting 3 results

Main effects In Eq. 3, we attempted to understand how the type of journal moderated the relationship between focal strategy areas and the performance of the article. We found that articles published in strategy-focused journals were relatively more impactful ($\beta = 0.45, p < 0.01$) on citations than the articles published in quant-focused journals. In relation to the direct effect of the strategy areas, results show that customer area ($\beta = 0.62, p < 0.1$) had a relatively greater impact on the citations than that of 4Ps strategy area.

Moderating effects If an article's focus was sales strategy and if the article was published in strategy-focused journals, it had a significantly lower impact ($\beta = -1.09, p < 0.01$) on citations than an article published in strategy-focused journals but the focus was on the 4Ps strategy. Further, an article focusing on other areas but published in the strategy-focused journal created higher citations than those focusing on 4Ps strategy ($\beta = 0.46, p < 0.05$). We did not find significant moderation effect of the journal type on the relationship between customer strategy ($\beta = -0.14, n.s.$) and citations.

Control effect Similar to setting 2, we found that if the data source used in the study was either primary ($\beta = 0.68, p < 0.01$), or secondary ($\beta = 0.43, p < 0.1$), it had a greater impact on the citation than that of other sources. Further, age of the article ($\beta = 0.031, p < 0.01$) contributed positively to the citations of the study. Finally, if the article was empirical in nature ($\beta = -0.42, p < 0.05$), it had a relatively lower impact on citation than a non-empirical article. In this context, we did not find any significant impact of other control variables.

Robustness analysis

To ensure that the results of the study were not governed by the selection of the dependent variables, we conducted two additional analyses. First, we estimated Eq. 1–3 using "log of (1 + Web of Science)" citations as the dependent variable. The results are largely consistent with our primary analysis results. Second, we re-estimated Eq. 1–3 using "total number of strategic contributions" as the dependent variable. Since "total number of strategic contributions" is a count variable, the use of OLS regression is not appropriate. Hence, we use a Poison Regression procedure in this context. Results from the Poison Regression are largely consistent with the primary analysis.

Discussion

This study attempts to provide additional insights to the debate in strategic marketing literature: What should be the approach of a marketing scholar, and what should get the preference in the marketing domain: methodological sophistication or strategic insights? While we agree that methodological sophistication should not eliminate the novelty of an idea, *the lack of methodological robustness may affect the ability to uncover strategic insights*. Consistent with the literature, we believe that the role of academic marketing is not only to enhance contributions in the theoretical and methodological domains but also to "strategic issues." In this study, we try to understand how different strategy areas generate impact, and how different models across articles, published in the top-tier marketing journals, moderate the relationship between strategy areas and impact (in terms of citations and strategic contributions) of the article. We also test for the moderating role of journal type and estimation approaches to better understand the impact of strategy areas on an article's impact.

By collecting data from 485 studies, we show that the articles focusing on the sales strategy area generated relatively lesser citations than articles in the 4Ps strategy area. This could be due to the niche area status for "sales" as well as the difficulty of getting data in this area. On the other hand, we found a significant positive impact of strategic research focusing on "customer" and "other area" with respect to the 4Ps area. Regarding the impact of models, it is interesting that SEM, multivariate analysis, and the linear models were pioneers in contributing to the citations. We further find that analytical models had not significantly impacted the citations with respect to other models. This is alarming such that in order to generate citations, an article does not have to adopt sophisticated models. We empirically show that rigor can be achieved using relatively simpler models proved to be evident from the impact of different models on citations.

Concerning the *moderating impact* of different models on the relationship between focal areas of research and citations, it is enlightening to find that different models had differential impacts on creating values across different focal areas. For example, in order to have higher citations, articles in the strategic research focusing on "customer" needed to adopt models such as linear models or SEM. On the other hand, the use of analytical models in the customer strategy area negatively influenced its ability to generate citations with regard to other models in the same strategy area. However, the observation is very different in the sales strategy area. While the use of "other models" could be beneficial, the use of multivariate analysis, analytical, and linear models actually reduced the citations if embedded in the strategic research focusing on "sales." Further, studies using SEM for strategic research in 'other areas' were more impactful in generating citations than studies using "other models" in "other areas." This discussion further tells us that model selection is critical for the performance of an article and it is important to align the models with the strategic research area of the study.

Complex estimation approach was not ideal for the impact of an article if the strategy research was focusing on "'sales" (with regard to the 4Ps strategy area). However, the use of complex estimation in the "customer" or "other" strategy areas benefitted an article in generating citations. This implies that it was beneficial to align the estimation approaches to focal areas of study in order to enhance the contributions of an article to the literature.

Further, the journal in which an article is published was critical for the contributions of the article. An article published in a strategy-focused journal had significantly higher citations than an article published in a quant-focused journal. Interestingly, an article focusing on "other strategy" but published in a strategy-focused journal produced higher citations than an article focusing on 4Ps strategy.

Finally, the age of the article matters, and the use of specific data could also contribute to the performance of the article. In the context of our study, we found that primary and secondary data sources had a significantly higher stake on the citations than that of data obtained from other sources. These insights could be helpful while developing an article.

Contributions

Our research makes three major contributions to the literature. First, we empirically show how different strategy areas of the articles influence the impact of the articles. We also show the need for aligning models to the focal strategy areas for higher impact. Second, we show that performance of an article is dependent on the journal in which the article is published. Finally, although methodological sophistication is desired for the growth of the marketing field, impact of an article is not conditional on model sophistication. Moreover, this study shows that an article could make an impact on the literature without embedding complexities.

This study is an attempt to understand the impact of the strategic marketing research on citations and the contingencies based on historic data more scientifically. The findings of this study point out that for an article to be more impactful, there should be an appropriate alignment between the strategic marketing areas and the models being used. It is advised that the results and the findings of this study should not be employed as guidelines to claim benefits and future predictions. This study does not advocate that simpler methods generate more citations/impact. On the contrary, this study cautions that both rigor and relevance are important for better performance and both should be exercised as per the need of the research questions related to the strategic marketing areas.

Limitations and future research directions

Although our research provides some novel insights to the literature, the study has multiple limitations. All the 485 papers included in this study were collected based on the defined criteria via various sources placing the keywords given in the literature for the focal areas. However, there is a probability of missing out on some studies attributed to the keywords that did not match. Future research may use an advanced algorithm to look at this limitation. We combined a few modeling approaches into a single group due to lack of observations. As a result, we are not able to tease out the effects of a few critical approaches (e.g., structural models, choice models, and panel data models). This study also envisages that models grouped in different categories may overlap with one another and limit the scope of the study. For example, "analytical models and game-theoretic models" or "choice models and non-linear models" are not mutually exclusive. To some extent, it limits the exquisiteness of the contributions of our study. Over time, researchers may collect more data points and test the individual impact of such methodological approaches. Again, we were forced to group sub-areas such as social media, firm, international marketing, branding, services, and innovation together to create "other strategy" due to data limitations. We recognize that this sort of grouping limits our ability to show the potential impact of these sub-areas on citations. Further, there may be a potential overlap among these areas. Future research may define theoretical logic for such grouping and/or attempt to uncover the individual impact of each of these areas. Further, we used a dummy variable for the estimation approach due to the lack of sufficient observations.

Future research can enhance the contribution by disentangling the unique effects of different estimation approaches. Additional data collection across other journals (e.g., *Journal of International Marketing*) will help researchers tease out the effects of individual areas, for example, branding, international marketing, etc. Our study is descriptive in nature and we do not make any causal arguments in our study (e.g., why the linear model has a greater impact than other models on citation). Future research can focus on the theoretical validation of our results. This study does not account for the "reputation of the authors," "evolution of the strategy areas" (e.g., old vs. new strategy areas), non-published works (which may lead to selection bias), as well as the "order of publication in an area" (e.g., first article published in 4Ps area). Future research can enhance the contribution by accounting for these variables.

Selection of a modeling approach for an article can be potentially endogenous. We agree that depending on the research questions, the context, data availability, as well as the need, models used across different strategy areas may not be in the researcher's control. Further, use of an estimation approach as well as acceptance in a journal (JM, JMR, etc.) is also not solely in the researcher's control. There can be a potential publication bias (e.g., focus of a journal, focus of an editor, etc.) too. Research questions, estimation approaches, and focal areas may also go hand-in-hand sometimes. Hence, the results discussed in this study are only indicative and should not be considered for normative implications**.** Future research can bring additional insights on the endogeneity and simultaneity issue. Through this study, we want to bring awareness to the fact that methodological sophistication does not necessarily result in a higher impact. The primary goal of any study should be in making the study methodologically rigorous and strategically relevant.

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